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An impact of EEG signals measuring time on motor imagery prediction accuracy

A research of the influence of electroencephalography signal measurements time on the accuracy of motor images prediction for an unmanned aerial vehicle brain-computer interface controlled application.

Introduction.

Steering of an unmanned aerial vehicle (UAV) by means of electroencephalography (EEG) and a brain-computer interface (BCI) is an innovative technology which provides an opportunity to steer external devices by means of brain activity (in thought) [1]. Process-specialized EEG-electrodes are placed on the user`s scalp in order to read-out the signals that indicate human`s different psycho-emotional states. Collected signals are processed by means of process-specialized software. This software filters noise and extracts useful signals that correspond to the user`s certain commands or intentions. This may include recognition of certain patterns of brain activity corresponding to UAV control commands. Interpreted signals are converted into commands. These commands are then transmitted to UAV. The UAV receives and executes these commands e.g. changes flight direction, ascends or descends, etc.

The goal of this research is to determine the most suitable duration of EEG signals measurements that should be taken in order to achieve a high-precision motor imagery commands recognition for unmanned aerial vehicle remote control applications.

Neural Network (NN) Model

Let's develop a model Fully connected deep neural network with 6 hidden layers (Fig.1). Input layer units count will be variable according to the size of the input sample. Output layer has 4 units, each representing the probability fraction of the classes. The objective of this NN model is classification.

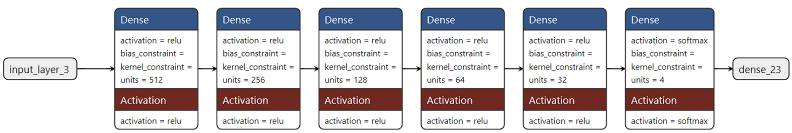

Fig. 1. NN model visualisation

The model is trained on “BCI Competition IV 2a: 4-class motor imagery” dataset [2]. This is a set of EEG data from 9 subjects. The BCI paradigm consists of four motor imagery tasks - imagination of movement of the left hand, right hand, both feet, and tongue - 4 classes in total. Here the very same data is used due to absence of publicly available data especially for UAV-steering. However this dataset has similarity with UAV-steering task, specifically - motor imagery task. This is why the results of this research can be used for developing UAV-steering neural networks models.

This dataset was reformatted for NN utilisation so as input train samples include signal EEG values from 22 electrodes for every time interval of corresponding duration for only a single test subject - patient id = 2, output train samples - categorical classes [3]. The chosen time intervals are shown in Table 1.

Table 1.

Recording time intervals

model	time (seconds)
1	0.02
2	0.08
3	0.2
4	0.4

According to every recording time interval a separate model with different Input layer units count is developed. For training 50 epochs and batch size 64 were chosen. Validation accuracy for every training epoch for every model is collected. The training result is displayed on the chart (Fig. 2).

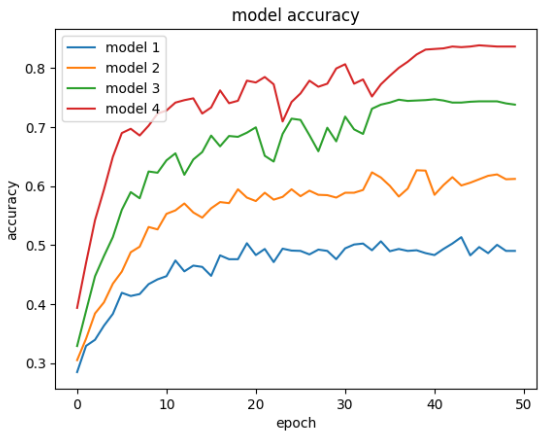

Fig. 2. Model accuracy

Let's evaluate models accuracy using test data (Table. 2.).

Table 2.

Accuracy evaluation on test data

model	accuracy
1	0.48046875
2	0.6266416311264038
3	0.7346024513244629
4	0.8413223028182983

Let's evaluate the performance of the models on data taken from another test subject - patient id = 3 (Table. 3.).

Table 3.

Accuracy evaluation on test data

model	accuracy
1	0.2517361044883728
2	0.23013699054718018
3	0.21583513915538788
4	0.24290220439434052

Conclusion. As it is seen from the results the bigger recording time provides better classification accuracy, i.e. the more input layer size is fed to the model the better is the accuracy. But for UAV-steering tasks a compromise between acceptable reaction time on control signals must be found. Also it should be noted that the model trained on EEG data of one user should not be used for another user, since their signals will differ almost every time.

References

1. Kamba Kalunga, Jeremie Otniel. Drone Control Using BCI Technology. 2023. Honors College Theses. 878. – 24 p.
2. Clemens Brunner, Robert Leeb, Gernot Müller-Putz. BCI Competition 2008–Graz data set A. IEEE Dataport. 2024. – 6 p. DOI: 10.21227/katb-zv89.
3. Navid Mohammadi Foumani, Lynn Miller, Chang Wei Tan, Geoffrey I. Webb, Germain Forestier, and Mahsa Salehi. Deep Learning for Time Series Classification and Extrinsic Regression: A Current Survey. 2023. – 47 p.